Kiel

Working Papers

Kiel Institute for the World Economy

Estimating the Marginal Abatement Costs of Carbon Dioxide Emissions in China: A Parametric Analysis

Limin DU,
Aoife HANLEY,
and Chu WEI

No. 1883 | November 2013

Web: www.ifw-kiel.de

Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany

Kiel Working Paper No. 1883 | November 2013

Estimating the Marginal Abatement Costs of Carbon Dioxide Emissions in China: A Parametric Analysis*

Limin DU, Aoife HANLEY, and Chu WEI

Abstract

This paper investigates the technical inefficiency, shadow price and substitution elasticity of CO_2 emissions of China based on a provincial panel for 2001-2010. Using linear programming to calculate a quadratic parameterized directional output distance function, we show that China's technical inefficiency increases over the period implying further scope for CO_2 emissions reduction in the medium and longer term at best by 4.5% and 4.9% respectively. Our results (notwithstanding regional differences) highlight increases in the shadow price of CO_2 abatement (1000 Yuan/ton in 2001 to 2100 Yuan/ton in 2010). Additionally, increasingly steep substitution elasticity highlights the difficult reality of reducing China's CO_2 emissions.

Keywords: CO_2 emissions; Shadow Price; Parametric Estimation; China

JEL: Q52; Q54; Q58

Limin DU

China Academy of
West Region Development,
Zhejiang University,
Hangzhou 310058, China
E-mail:
dlmsos@hotmail.com

Aoife HANLEY

Christian Albrecht University Kiel
Institute for the World Economy,
Kiel 24105, Germany
E-mail:
aoife.hanley@ifw-kiel.de

Chu WEI

Corresponding author:
School of Economics,
Renmin University of China,
Beijing 100872, China
Tel: +0086 18811553981
E-mail:
xiaochu1979@hotmail.com

*We truthfully appreciate the comments and suggestions from the participants of the seminar in Kiel Institute for the World Economy. Limin DU gratefully acknowledges the financial support from the Ministry of Education of the People's Republic of China (13YJA790015), the Natural Science Foundation of Zhejiang Province in China (LQ12G03013), and the Fundamental Research Funds for the Central Universities.

1. Introduction

The international community has become increasingly concerned about rising carbon dioxide (CO_2) emissions that have risen in parallel with China's strong growth (Rosenthal, 2008). In 2009, the total CO_2 emissions of China reached 7.7 billion tons, accounting for roughly 24% of total global emissions[1]. As one of the leading CO_2 emitters in the world, China has become the focus for global greenhouse gas abatement.

The Chinese government has set about reducing its greenhouse gas emissions. In 2009, the central government of China declared its target for limiting greenhouse gas emissions, namely to reduce the carbon intensity (CO_2 emissions per unit GDP) by 40-45% by the year 2020, compared with 2005 levels. Under the 12th Five Year Plan, China furthermore set a carbon intensity reduction target of 17% to be achieved by 2015, compared with 2010 levels[2].

But what scope do China's industries have to curb these emissions without damaging economic growth? Being able to properly assess the marginal abatement costs is an important first step for global climate negotiations with China. Not only because helps China's international partners to persuade China of the need to curb emissions but it helps inform the debate by guiding the choice of a more efficient burden-sharing rule and abatement mechanism. Importantly for China, an accurate cost assessment helps to shape a broad range of domestic environmental policy issues, i.e., it can be used to guide carbon tax rate setting, emission permits trading and regional allocation of reduction obligation, etc. (Färe et al., 1993; Wei et al., 2013).

This is the question that our analysis sets out to answer. There is some evidence at the firm level, industrial level or provincial level for earlier time periods shedding light on China's CO_2 abatement cost, but most of those studies have approached the question using non-parametric method or parametric Shephard distance function respectively. Our analysis draws on the novel and more flexible parametric directional output distance function approach which allows us to capture the advantages of differentiability and non-proportional

[1] The data is derived from the World Bank, http://data.worldbank.org/indicator/EN.ATM.CO2E.KT?display=graph.

[2] For those not familiar to China's Five Year Plans, these are a series of economic and social development initiatives, which outline the directions, targets and methods of development. The first Five Year Plan begins in 1953, and the most recent one is the 12th Five Year Plan covering the year 2011-2015.

changes in outputs (simultaneous contraction of bad output and expansion of good output). These properties are particularly attractive, since the former promises the uniqueness of shadow price while the latter does not rule out a 'double-dividend' of emissions reduction and economic growth which is what the policy-makers are generally interested in.

We find that the environmental technical inefficiency of China increases for the whole sample period and it is possible for China to further reduce the CO_2 emissions by 4.5% in the 10th Five Year Plan and 4.9% in the 11th Five Year Plan if all the provinces produce on the production frontier. The shadow price of CO_2 reduction in China also increases continuously for the whole sample period with regional differences, corresponding to an annual growth rate of 8%, but the growth speed in the 11th Five Year Plan is much higher than that in the 10th Five Year Plan. The increasing absolute value of substitution elasticity indicates the difficult reality of reducing China's CO_2 emissions.

The remainder of the paper is organized as follows: section 2 reviews the previous literature. Section 3 is the theoretical model. Section 4 presents the empirical specifications. Section 5 describes the data. Section 6 reports the estimation results. We conclude in the last section.

2. Literature Review

Recent developments in shadow prices of non-marketed pollutants allow the researchers to estimate the marginal abatement cost of CO_2 reduction without price and cost information (Färe et al., 1993; Färe et al., 2005)[3]. Typically, the analysis is performed by modeling pollutants as by-product bad outputs under a multi-input multi-output environmental production technology framework. Then the output distance function is employed to derive the shadow prices of CO_2 reductions by using the duality between the output distance function and the revenue function.

There are two widely used output distance functions in previous studies. The Shephard output distance function assumes a proportional adjustment for all outputs (Shephard et al.,

[3] Integrated system models also have been employed to estimate the marginal abatement cost of CO_2 reductions, see Zhang and Folmer (1998), Criqui et al. (1999), Tol (1999), Chen (2005), Morris et al. (2012), etc. The most controversial aspects of these models are settings of the baseline scenarios and structural characteristics of the models (Fischer and Morgenstern, 2006; Marklund and Samakovlis, 2007).

1970). In contrast, the newly developed directional output distance function allows a simultaneous expansion of good outputs and contraction of bad outputs along the given direction (Chambers et al., 1998; Chung et al., 1997) [4]. Relatively speaking, the directional output distance function is a more appropriate metric for measuring performance in the presence of bad output under regulation (Färe et al., 1993; Färe et al., 2005).

There are two strategies to estimate the output distance function and shadow price. One is the non-parametric approach, namely Data Envelopment Analysis (DEA), which constructs the output possibility set as a piecewise linear combination of all observed outputs and inputs. It is a data-driven technique and has been widely used in efficiency evaluation (Boyd et al., 1996; Boyd et al., 2002; Färe et al., 2007; Lee et al., 2002; Maradan and Vassiliev, 2005) . However, the distance function estimated via DEA method is not differentiable, thus it is less well-suited to the estimation of shadow prices and elasticity of substitutions (Färe et al., 2005). Additionally, the DEA methods are plagued with a number of other inaccuracies, such as how to deal with outliers (Vardanyan and Noh, 2006).

Apart from DEA, parametric estimation represents a further method to investigate environmental bads. It pre-assumes a specific functional form for the distance function and then estimates the parameters of the distance function. Once the parameters have been estimated, it is easy to calculate values of the distance function, the shadow price and the substitution elasticity. In empirical analysis, the Shepherd output distance function is usually specified as a translog functional form, while the directional output distance function is usually specified as a quadratic functional form[5]. In the past two decades, a large number of studies emerged to investigate the marginal abatement cost of various pollutants with the parametric method (Coggins and Swinton, 1996; Färe et al., 1993; Färe et al., 2005; Färe et al., 2006; Murty et al., 2007; Reig-Martínez et al., 2001; Swinton, 1998, 2002, 2004; Vardanyan and Noh, 2006).

However, only a few papers have investigated the marginal abatement cost of CO_2 emissions directly for China[6]. In these previous studies, both parametric and non-parametric

[4] Essentially, the directional output distance function is a complete generalization of the Shephard output distance function.

[5] It is not feasible to specify the directional output distance function as a translog functional form since the translation property of the directional output distance function will be violated.

[6] Some papers investigate the marginal abatement cost of SO_2 emissions in China, such as Ke et al. (2008), Kaneko et al. (2010),

methods have been used, but there is little consensus on the magnitude of the estimated shadow prices which are widely dispersed.

Some studies focus on industrial level or firm level shadow prices estimations. Lee and Zhang (2012) estimate the shadow prices of CO_2 emissions for 30 Chinese manufacturing industries in 2009, based on a parametric Shephard/translog specification. Their results show that the shadow prices vary from a high of 18.82 dollars/ton to a low of zero, with an average of 3.13 dollars/ton. Yuan et al. (2012) estimate the shadow prices of CO_2 reductions for the industrial sector in China applying DEA and they find that the shadow prices are lie a range of 200 Yuan/ton to 0.12 million Yuan/ton. Wei et al. (2013) investigate the shadow prices of Chinese thermal power enterprise in 2004, using a parametric quadratic functional form. Their findings suggest that the shadow price for a representative power enterprise in Zhejiang reaches a mean of 2059.8 Yuan/ton.

Some studies focus on provincial level shadow price estimations. Wang et al. (2011) find that the average provincial shadow price of CO_2 reduction is about 475 Yuan/ton in 2007, based on the directional distance function and non-parametric DEA method. Choi et al. (2012) estimate the provincial marginal abatement costs of CO_2 emissions of China for the year 2001-2010, by employing a slack-based DEA model. They find that the average shadow price of CO_2 emissions in China has increased gradually from 6.94 dollars/ton in 2001 to 7.44 dollars/ton in 2010. Wei et al. (2012) report a mean shadow price of 114 Yuan/ton for 29 provinces in China over period 1995-2007, based on a slack-based DEA approach.

From the above literature, we find that all of the previous studies on the provincial shadow price of CO_2 reduction in China are based on non-parametric DEA methods or parametric Shephard/translog specifications. As we have mentioned above, the non-parametric DEA method is less well-suited to the estimation of the shadow price and substitution elasticity because of its non-differentiability, whereas the parametric Shephard/translog specification confines itself to the case of proportional adjustment of good and bad outputs. Accordingly, the translog specification is not an appropriate metric for measuring performance changes where bad outputs are subject to outside regulation.

The novelty of our paper is to investigate, for the first time, provincial shadow prices of

Ke et al. (2010), Tu (2010), etc.

CO_2 reductions in China based on a more reliable directional output distance function which is estimated parametrically. Furthermore, we estimate the provincial Morishima substitution elasticity for China. In so doing, we aim to provide new insights to inform the debate on an optimal emissions policy in China.

3. Theoretical Model

What follows is the theoretical model underpinning our approach. We start by introducing the directional output distance function, and then deriving shadow prices of bad outputs and the Morishima substitution elasticity.

3.1 Directional Output Distance Function

Suppose that a producer employs a vector of inputs $x = (x_1, ..., x_N) \in \mathrm{R}_+^N$ to produce a vector of good outputs $y = (y_1, ..., y_M) \in \mathrm{R}_+^M$ and a vector of bad outputs $b = (b_1, ..., b_J) \in \mathrm{R}_+^J$. Production technology can be defined as the following output set:

$$P(x) = \{(y,b) : x \text{ can produce } (y,b)\} \qquad (1)$$

Besides the standard assumptions of compact and freely disposable in inputs, we need to impose some additional assumptions on the output set. First, we assume that the bad outputs are jointly produced with the good outputs. Formally, if $(y,b) \in P(x)$ and $b = 0$, then $y = 0$, which implies that no good output can be produced without simultaneously creating bad output. Second, we assume that good outputs and bad outputs are together weakly disposable, i.e., if $(y,b) \in P(x)$ and $0 \le \theta \le 1$, then $(\theta y, \theta b) \in P(x)$. Weak disposability means that any proportional reduction of good and bad outputs together is feasible, which implies any reduction of bad output carries a cost. At the same time, we retain the traditional assumption that good outputs by themselves are freely disposable. Formally, free disposability implies that if $(y,b) \in P(x)$ and $y' \le y$, then $(y',b) \in P(x)$. This indicates that it is always possible to dispose of some of good outputs without incurring an extra cost.

The directional output distance function represents in function form the production technology in line with the above assumptions. Formally, the directional output distance function is defined as

$$\vec{D}_o(x, y, b; g_y, -g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \qquad (2)$$

where $g = (g_y, g_b) \in \mathrm{R}_{+}^{M} \times \mathrm{R}_{+}^{J}$ is a directional vector which specifies the direction of the output vector. The directional distance function describes the simultaneous maximum expansion of good outputs and contraction of bad outputs that is feasible for any given production technology.

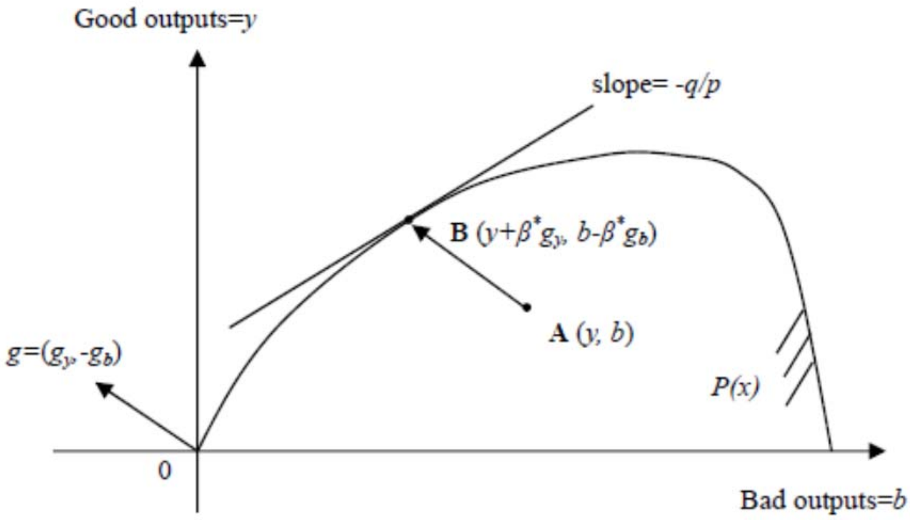

Figure 1: Directional Output Distance Function

Figure 1 depicts such a function. Given the production technology *P*(*x*) and the direction vector $g = (g_y, g_b) > 0$, the directional output distance function expands good output *y* and contracts bad output *b* in the *g* direction until it reaches the boundary of *P*(*x*). For an observation *A*(*y, b*) that lies within production set *P*(*x*), it is possible to increase *y* and reduce *b* simultaneously before hitting the boundary of the production set at point $B\left(y + \beta * g_y,\ b - \beta * g_b\right)$, where $\beta^* = \vec{D}_o(x, y, b; g_y, -g_b)$.

The directional output distance function describes inefficiency. A zero value of β means that this producer is located on the frontier, while a positive value of β reflects the existence of inefficiency. The producer can achieve an expansion of good output and simultaneously reduce bad output in order to reach the frontier in the *g* direction. A higher value of β implies higher inefficiency, in other words, lower efficiency.

The directional output distance function inherits its properties from the output set *P(x)*. According to Färe et al. (2005), these properties include:

a) $\vec{D}_o(x,y,b;g_y,-g_b)\ge 0$ if and only if (y,b) is an element of $P(x)$

b) $\vec{D}_o(x,y',b;g_y,-g_b)\ge \vec{D}_o(x,y,b;g_y,-g_b)$ for $(y',b)\le(y,b)\in P(x)$

c) $\vec{D}_o(x,y,b';g_y,-g_b)\ge \vec{D}_o(x,y,b;g_y,-g_b)$ for $(y,b')\ge(y,b)\in P(x)$

d) $\vec{D}_o(x,\theta y,\theta b;g_y,-g_b)\ge 0$ for $(y,b)\in P(x)$ and $0\le\theta\le 1$

e) $\vec{D}_o(x,y,b;g_y,-g_b)$ is concave in $(y,b)\in P(x)$

The first property indicates that $\vec{D}_o(x,y,b;g)$ is non-negative for feasible output vectors. The second property implies that $\vec{D}_o(x,y,b;g)$ is monotonic in good outputs. The third states that if bad outputs increase, holding inputs and good outputs constant, inefficiency does not decrease. The fourth property corresponds to weak disposability of good and bad outputs. The last property helps us to determine the sign of the output elasticity of substitution.

Additionally, it is easy to verify that the directional distance function also satisfies the translation property:

$$\vec{D}_o(x,y+\alpha g_y,b-\alpha g_b;g_y,-g_b)=\vec{D}_o(x,y,b;g_y,-g_b)-\alpha \tag{3}$$

where α is a scalar. This property means that if desirable output is expanded by αg_y and undesirable output is contracted by αg_b simultaneously, then the resulting value of the directional output distance function will be reduced by α, or in other words, the inefficiency of the decision-making unit (DMU) will be reduced by the amount α.

3.2 Shadow Prices of bad outputs

To derive the shadow prices, we need to evoke the duality between the directional output distance function and the revenue function.

Following Färe et al. (2006), we specify the revenue function of a DMU as follows:

$$R(x,p,q)=\max_{y,b}\{py-qb:\vec{D}_o(x,y,b;g)\ge 0\} \tag{4}$$

where $p=(p_1,\dots,p_M)\in \mathbb{R}_+^M$ and $q=(q_1,\dots,q_J)\in \mathbb{R}_+^J$ are the prices of good and bad outputs respectively. The revenue function describes the largest feasible revenue obtainable when the producer is faced with good output prices p and bad output prices q respectively.

If an output vector (*y, b*) is feasible, then the elimination of any inefficiency associated with that output vector by moving in the direction *g* is also feasible, i.e. if $(y,b)\in P(x)$, then $(y+\beta g_y, b-\beta g_b)\in P(x)$. Thus, given a feasible directional vector $g=(g_y,g_b)$, we have

$$R(x,p,q)\geq (py-qb)+p\cdot\vec{D}_o\left(x,y,b;g\right)\cdot g_y+q\cdot\vec{D}_o\left(x,y,b;g\right)\cdot g_b \tag{5}$$

The left side of equation (5) represents maximal feasible revenue while the right side corresponds to observed revenue plus technical efficiency gains. The improvement in technical efficiency can be decomposed into two components, the gain due to an increase in good outputs along g_y and the gain due to a decrease in bad outputs along g_b.

Rearranging the formula (5), we have

$$\vec{D}_o\left(x,y,b;g\right)\leq\frac{R(x,p,q)-(py-qb)}{p\cdot g_y+q\cdot g_b} \tag{6}$$

Therefore, the directional output distance function can be derived from the revenue function.

$$\vec{D}_o\left(x,y,b;g\right)=\min_{p,q}\left\{\frac{R(x,p,q)-(py-qb)}{p\cdot g_y+q\cdot g_b}\right\} \tag{7}$$

Applying the envelope theorem twice to Equation (7), we get two first-order conditions:

$$\nabla_y\vec{D}_o\left(x,y,b;g\right)=\frac{-p}{p\cdot g_y+q\cdot g_b} \tag{8}$$

$$\nabla_b\vec{D}_o\left(x,y,b;g\right)=\frac{q}{p\cdot g_y+q\cdot g_b} \tag{9}$$

Given the market price of the *m*-th good output, we are able to derive the shadow price of the *j*-th bad output.

$$q_j=-p_m\left[\frac{\partial\vec{D}_o(x,y,b;1,-1)/\partial b_j}{\partial\vec{D}_o(x,y,b;1,-1)/\partial y_m}\right], j=1,\ldots,J \tag{10}$$

As shown in Figure 1 for the case of one good output and one bad output, the ratio of the shadow price (-*q/p*) for an observation with coordinates (*y, b*) describes the slope of the tangent line at the boundary of *P*(*x*). It reflects the trade-off between the bad and good output respectively on the frontier of *P(x)* where the production is technically efficient.

3.3 Morishima Elasticity of Substitution

It is important to investigate how the good-bad output ratio of shadow price (the curvature of the boundary of the production set) changes as the relative pollution intensity (ratio of bad output to good output) changes. This basic idea underpins the Morishima shadow price output elasticity of substitution (Blackorby and Russell, 1981).

Following Färe et al. (2005), the Morishima elasticity is defined as:

$$M_{by} = \frac{\partial \ln(q/p)}{\partial \ln(y/b)} \tag{11}$$

Equation (11) can be specified in terms of the directional output distance function as

$$M_{by} = y^* \left[\frac{\partial^2 \vec{D}_o\left(x, y, b; g\right)/\partial b \partial y}{\partial \vec{D}_o\left(x, y, b; g\right)/\partial b} - \frac{\partial^2 \vec{D}_o\left(x, y, b; g\right)/\partial y \partial y}{\partial \vec{D}_o\left(x, y, b; g\right)/\partial y} \right] \tag{12}$$

where $y^* = y + \vec{D}_o\left(x, y, b; 1, -1\right)$. It is easy to prove that the sign of M_{by} is negative under certain conditions. Values of M_{by} that are more negative indicate that a given change in the ratio of good output and bad output (*y/b*) will result in higher corresponding changes in the shadow price ratio of bad to good outputs (*q/p*). That is to say that as the Morishima elasticity M_{by} becomes more negative it becomes more costly for the DMU to reduce the bad output.

4. Empirical Specifications

As we have mentioned above, the directional output distance function can be alternately estimated parametrically or non-parametrically. In this study, we adopt the parametric approach because of its advantage of differentiability. Following Chambers et al. (1998), Färe et al. (2005) and Murty et al. (2007), we employ the quadratic form to parameterize the directional output distance function. The quadratic function satisfies the translation property and is twice differentiable and flexible. As Färe et al. (2005) have suggested, we set the directional vector $(g_y, g_b) = (1,1)$ to seek a simultaneous expansion of good output and reduction of bad output.

We consider the case of three inputs, one good output and one bad output. Assume that there are k=1,...,K provinces producing in t=1,...,T years. Then, the quadratic directional output distance function for province k in year t can be represented as

$$\begin{aligned}\vec{D}_o(x_k^t, y_k^t, b_k^t; 1, -1) &= \alpha + \sum_{n=1}^{3} \alpha_n x_{nk}^t + \beta_1 y_k^t + \gamma_1 b_k^t + \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3} \alpha_{nn'} x_{nk}^t x_{n'k}^t \\ &+ \frac{1}{2}\beta_2 (y_k^t)^2 + \frac{1}{2}\gamma_2 (b_k^t)^2 + \sum_{n=1}^{3} \eta_n x_{nk}^t b_k^t + \sum_{n=1}^{3} \delta_n x_{nk}^t y_k^t + \mu y_k^t b_k^t\end{aligned} \tag{13}$$

To capture the province and time effect, we add a set of province dummy variables and time dummy variables in the intercept term of equation (13) as Färe et al. (2006) have done:

$$a = a_0 + \sum_{k=1}^{K-1} \lambda_k S_k + \sum_{t=1}^{T-1} \tau_t T_t \tag{14}$$

where λ_k and τ_t are the coefficients of the dummy variables. The province dummy variable $S_{k'} = 1$ if $k' = k$ and 0 otherwise. Similarly, the time dummy variable $\tau_{t'} = 1$ if $t' = t$ and 0 otherwise.

Following the work of Aigner and Chu (1968), we employ a deterministic linear programming algorithm to estimate the parameters of Equation (13) by minimizing the sum of the deviations of the estimated directional output distance functions from that of the frontier. The advantage of this approach is that it allows us to impose parametric restrictions on the quadratic functional form[7].

[7] The directional output distance function also can be estimated as a stochastic frontier, but this method cannot impose the constraints on the econometric estimation and only can test the constraints ex-post.

$$
\begin{aligned}
&\min \sum_{t=1}^{T}\sum_{k=1}^{K}(\vec{D}_o(x_k^t, y_k^t, b_k^t;1,-1)-0) \\
&s.t.\ (i)\ \ \vec{D}_o(x_k^t, y_k^t, b_k^t;1,-1) \geq 0, k=1,...K; t=1,...,T \\
&\qquad (ii)\ \vec{D}_o(x_k^t, y_k^t, 0;1,-1) < 0, k=1,...K; t=1,...,T \\
&\qquad (iii)\ \frac{\partial \vec{D}_o(x_k^t, y_k^t, b_k^t;1,-1)}{\partial b} \geq 0, k=1,...K; t=1,...,T \\
&\qquad (iv)\ \frac{\partial \vec{D}_o(x_k^t, y_k^t, b_k^t;1,-1)}{\partial y} \leq 0, k=1,...K; t=1,...,T \\
&\qquad (v)\ \frac{\partial \vec{D}_o(\bar{x}, y_k^t, b_k^t;1,-1)}{\partial x_n} \geq 0, n=1,2,3; k=1,...K; t=1,...,T \\
&\qquad (vi)\ \beta_1-\gamma_1=-1, \beta_2=\gamma_2=\mu, \delta_n-\eta_n=0, \quad n=1,2,3 \\
&\qquad (vii)\ \alpha_{n,n'}=\alpha_{n',n}, \quad n,n'=1,2,3
\end{aligned} \tag{15}
$$

The first set of restrictions (i) ensures that all observations are feasible. This implies that each observation is located either on or below the boundary. The null-jointness property is imposed by the restrictions in (ii), which means that, for *y>0*, the output bundle *(y, 0)* is not technically feasible (Marklund and Samakovlis, 2007). The monotonicity assumption in bad and good outputs is imposed by the inequality (iii) and (iv) respectively, which ensures the correct sign of the calculated shadow prices. Following Färe et al. (2006), we also impose positive monotonicity constraints on the inputs for the mean level of input usage in (v), which means that, at the mean level of inputs, an increase in input usage holding good and bad outputs constant causes the directional output distance function to increase. The parameter restrictions given by (vi) impose translation property. Additionally, the symmetry restrictions are imposed in (vii).

Once the parameters of the directional output distance function have been estimated, we are able to calculate the shadow price of the bad output and Morishima substitution elasticity for each province in each year. The shadow price of the bad output can be written as

$$
q=-p\frac{\gamma_1+\gamma_2 b+\sum_{n=1}^{3}\eta_n x_n+\mu y}{\beta_1+\beta_2 y+\sum_{n=1}^{3}\delta_n x_n+\mu b} \tag{16}
$$

and the Morishima substitution elasticity can be written as

$$M_{by} = y * \left[\frac{\mu}{\gamma_1 + \gamma_2 b + \mu y + \sum_{n=1}^{N} \eta_n x_n} - \frac{\beta_2}{\beta_1 + \beta_2 y + \mu b + \sum_{n=1}^{N} \delta_n x_n} \right] \quad (17)$$

5. Data and Descriptive Statistics

We consider the case of one good output, annual regional Gross Domestic Product (***Y***), one bad output, carbon dioxide emissions (***B***), and three inputs, labor (***L***), capital (***K***) and energy (***E***). Our data is provincial level aggregate data that covers 30 provinces of China. Given that China's energy-conservation and pollutant-abatement program was launched at the beginning of 2001, our sample covers the period 2001-2005 (10th Five Year Plan) and 2006-2010 (11th Five Year Plan), constituting a province-by-year panel dataset[8].

To eliminate the influence of inflation, we deflate GDP to the 2005 price. The input of labor force is measured as number of employed persons at the end of each year. The data of GDP and labor input are both obtained from the *China Statistical Yearbook*. Energy consumption is measured in standard coal equivalent, and the data is collected from the provincial statistical yearbooks.

The data of capital stock is not directly available from any of the statistical yearbooks. However, we can estimate it by the following perpetual inventory method:

$$K_{i,t} = K_{i,t-1}(1-\rho_i) + I_{i,t} \quad (18)$$

where $I_{i,t}$ and $K_{i,t}$ are gross investment and capital stock for province *i* in year *t*, $K_{i,t-1}$ is the capital stock of province *i* in year *t-1*, and ρ_i is depreciation rate. The values of initial capital stock and depreciation rate are derived from Zhang et al. (2004), while the data of annual investment is derived from the *China Statistical Yearbook*. Similarly, we depreciate the data to the 2005 price.

The data of CO_2 emissions is neither directly available. Following the method provided by IPCC (2006), we estimate the CO_2 emissions emitted through the burning of fossil fuels by the following formula:

$$CO_2 = \sum_{i=1}^{6} E_i \times CF_i \times CC_i \times COF_i \times (44/12) \quad (19)$$

[8] Tibet is excluded because of the problem of data availability.

where i is the index of different types of fossil fuel, including coal, gasoline, kerosene, diesel, fuel oil and natural gas. The variables E_i, CF_i, CC_i and COF_i represent total consumption, transformation factor, carbon content and carbon oxidation factor of fuel i, respectively. The term 44/12 is the ratio of the mass of one carbon atom combined with two oxygen atoms to the mass of an oxygen atom. The data of provincial fuel consumption are taken from the regional energy balance tables in the *China Energy Statistical Yearbook.* The other coefficients needed are derived from Du et al. (2012).

Table 1: Summary Statistics for Inputs and Outputs, 2001–2010

Region	Inputs			good output	bad output
	Labor (10000 persons)	Capital (100 million Yuan)	Energy (10000 tons)	GDP (100 million Yuan)	CO_2 emissions (10000 tons)
China	2301	15808	8921	7535	16949
	(1523)	(13857)	(6336)	(6903)	(12437)
#East	2495	24427	11721	12180	21639
	(1704)	(17365)	(8122)	(8778)	(15864)
#Middle	2758	13831	9054	6642	18231
	(1434)	(8594)	(4250)	(3410)	(8730)
#West	1775	8628	6025	3540	11326
	(1223)	(6463)	(3831)	(2598)	(7881)

Note: standard deviation in parenthesis.

Table 1 lists the descriptive statistics of inputs and outputs for China and three different regions.[9] The means and standard deviations of the variables are reported in the table. From Table 1, we can observe that the means of GDP and capital stock in east region are both much higher than that of middle and west regions. Meanwhile, the east region consumes a higher amount of energy and emits more CO_2 emissions.

[9] East region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. Middle region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. West region includes Inner Mongolia, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

6. Empirical Results

To avoid the convergence problem, we normalize the data by dividing each output and each input by their mean values respectively (Färe et al., 2005). This normalization means that $(x,y,b)=(1,1,1)$ for a hypothetical province using mean input to produce mean outputs.

6.1 Technical Inefficiency

The parameter estimates for the quadratic functional form of the directional distance function (13) are obtained by solving the linear programming (15) using *MATLAB* (the estimated parameters are reported in Appendix Table 1A). Once the parameters are obtained, we are able to calculate the directional output distance functions for each province in each year by inserting the estimated parameters back into the equation (13). The directional output distance function serves as a measure of technical inefficiency since it gives the maximum unit expansion of the good output and contraction of the bad output. If the directional distance function equals zero, then we say that the production is fully efficient. A positive score means the presence of inefficiency in the production process. A higher score of the directional output distance function means a higher technical inefficiency.

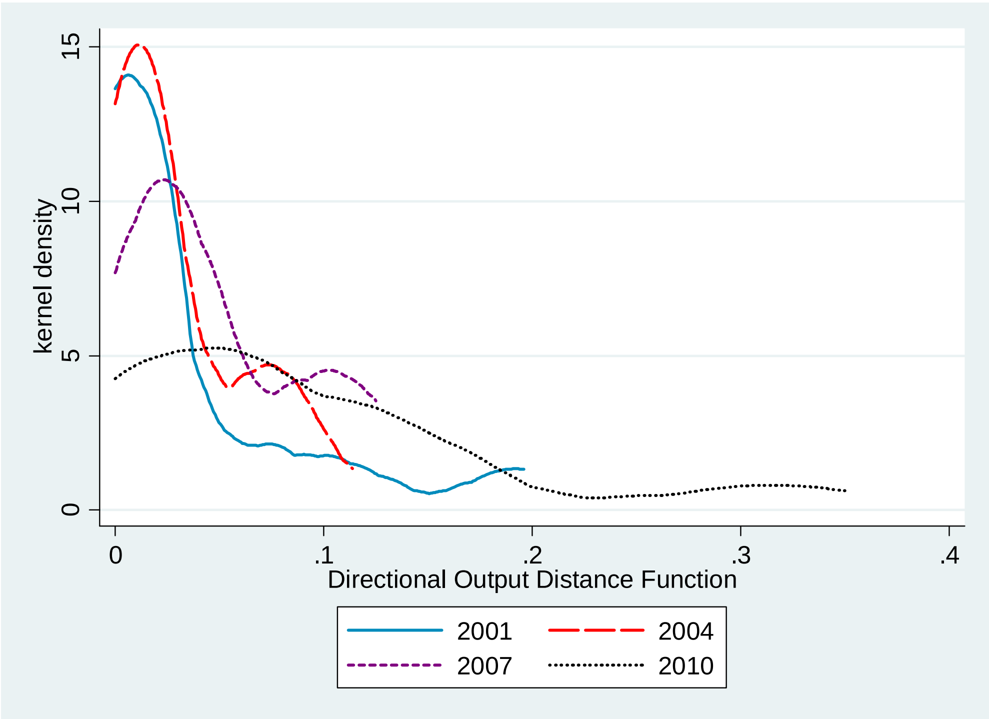

Figure 2: Kernel Density of Directional Output Distance Functions

Figure 2 plots the kernel densities of the estimates of provincial directional output distance functions for selected years (more detailed estimation results are reported in Appendix Table 2A)[10]. From Figure 2, we can observe that the kernel density curves move rightward. The peaks of the curves become lower and the directional output distance functions become more dispersed as time elapses, indicating that the mean and variance of the technical inefficiency have increased during the period 2001 to 2010.

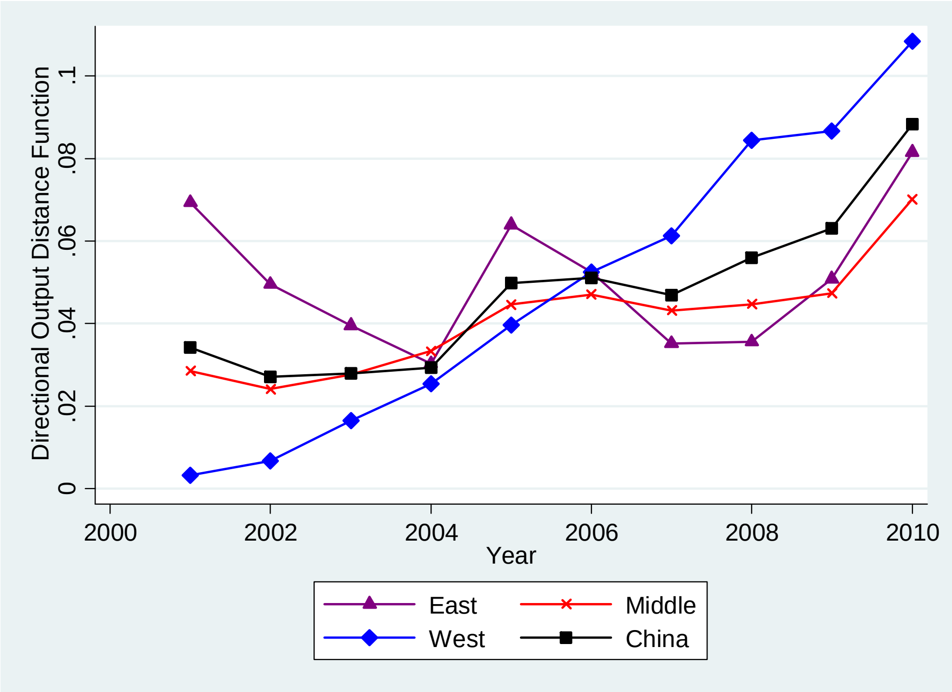

Figure 3: Average Technical Inefficiency by Region

Figure 3 further reports the average values of directional output distance functions of the three different regions and the whole country (more detailed results are reported in Appendix Table 2A). From Figure 3, we can observe that the average technical inefficiency of the whole country of China has increased for almost the whole sample period. The dynamic trends of the average technical inefficiency for the three regions show great disparity. The curve for the east region fluctuated, while that of the west and middle regions, especially for the west region, increased sharply and continuously for the whole sample period. We also can find that the average technical inefficiency of the east region is much higher than that of the west and middle regions during the period 2001 to 2010.

Traditionally, the east region of China becomes much more developed than the west

[10] Epanechnikov kernel function and optimal bandwidth are used.

and middle regions following the economic reform of 1978. To achieve more balanced regional development, the central government of China began to implement a so-called "Western Development" program after 2000. The development of middle region has also been a focus for policymakers since 2004. Many energy-intensive firms formerly located in the east region have been moved to the west and middle regions since then, while the east region has increasingly increased its composition of service and high-tech firms. Thus, it is not surprising that the average inefficiency seen in the west and middle regions has increased more rapidly than that of the east region. In essence, what Figure 3 highlights is the evolving composition of China's industry with the displacement of heavy industry to the Western region.

6.2 Reduction Potential of CO_2 Emissions

The derived values of directional output distance functions allow us to further measure the feasible reduction potentials of CO_2 emissions by the following formula:

$$\Delta b_{it} = b_{it} - (b_{it} - \beta_{it} g_b) \tag{20}$$

where b_{it} and β_{it} are the quantity of CO_2 emissions and the estimated technical inefficiency score of province *i* in year *t*, and g_b is the directional vector for the bad output. $b_{it}^* = (b_{it} - \beta_{it} g_b)$ is the minimum attainable level of emissions for province *i* in year *t* when production processes are fully efficient. There is considerable heterogeneity among the provinces when it comes to the scale of potential emissions. This makes it difficult to compare each province's relative ability to reduce emissions based on its size and output. To facilitate this comparison, we take the scale of potential emissions (estimated) and divide it by the real observed emissions for each province. This gives us a ratio which can be used to compare across regions.

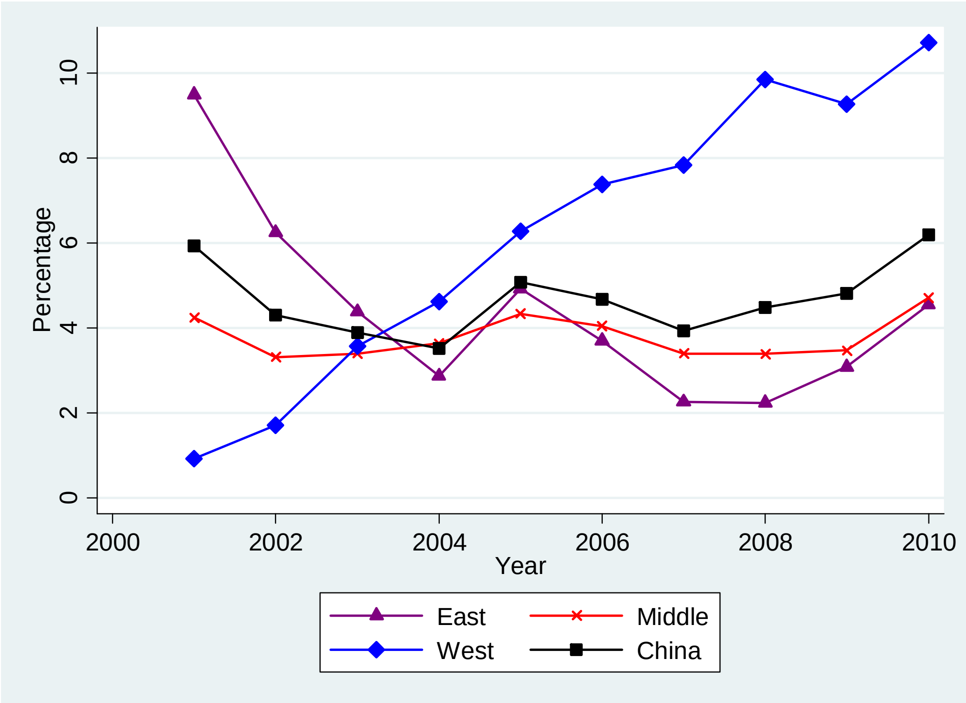

Figure 4: Average Reduction Potential by Region

Figure 4 plots the within-region abatement potential ratio for the three regions and the whole country[11]. From Figure 4, we can observe that the patterns of the abatement potential ratios reflect the data for technical inefficiencies. It is not surprising since the abatement potential ratios are calculated from technical inefficiency scores. At the country level, the percentages of abatement potential ratios fluctuate between about 4-6%, which indicates that it is possible for China to further reduce about 4-6% of CO_2 emissions conditioned on all provinces producing at their most efficient level.

6.3 Shadow Prices of CO_2 Emissions

According to equation (16), if the parameters and the price of the good output are known, then we may compute the absolute price for the bad output. We need to inflate the formula by multiplying by the ratio of the mean value of GDP to the mean value of CO_2 emissions since we have normalized the input and output data. Without loss of generality, the price of the good output, GDP, can be set to be 1.

[11] More detailed analytical results are available from the authors on request.

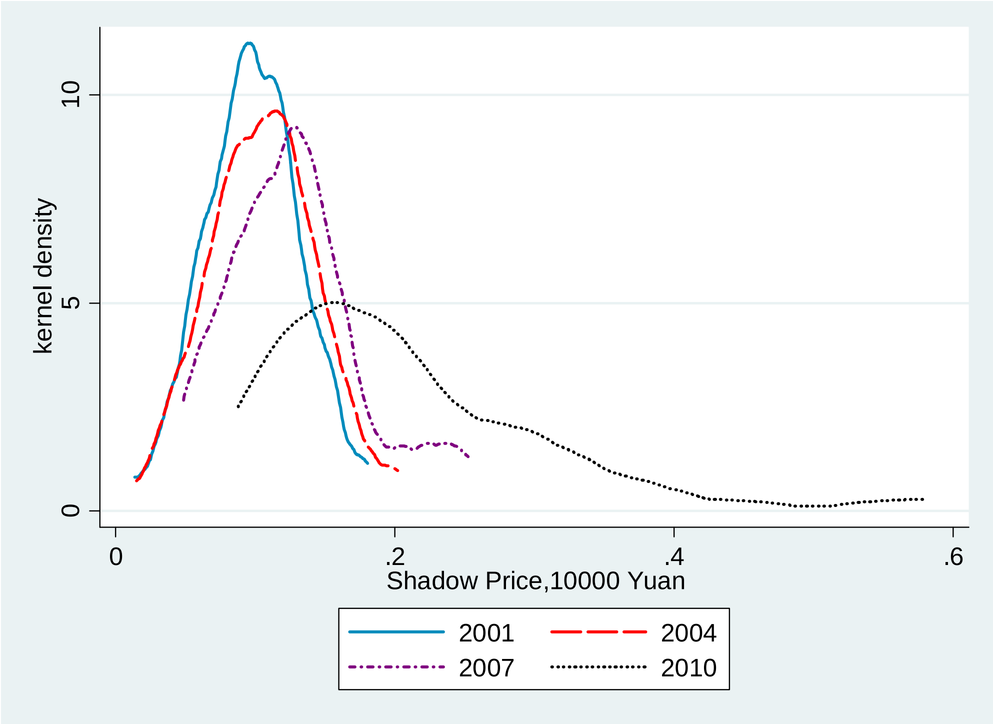

Figure 5: Kernel Density of Shadow Price

Figure 5 plots the kernel densities of the shadow prices for selected years. From the figure, we can observe that the kernel density curves shift rightward over time, and the dispersion range of points becomes wider, indicating that the mean value and the variance of the shadow prices have increased. In 2001, the shadow price has a mean of 1000 Yuan/ton and ranges from 100 Yuan/ton (Henan) to 1800 Yuan/ton (Shanghai). The distribution of shadow price in 2010 seems significantly differ from the 2001 case. To cut an additional ton of CO_2 emissions by the end of 2010, the cost rises to 2100 Yuan. The spectrum of shadow price in 2010 exhibits a greater variation, ranging from 900 Yuan/ton (Guizhou) to 5700 Yuan (Jiangsu). For the year 2001, 2004 and 2007, the shadow prices of most of the provinces are lower than 2000 Yuan, but the number of the provinces with a shadow price higher than 2000 Yuan increased dramatically in 2010.

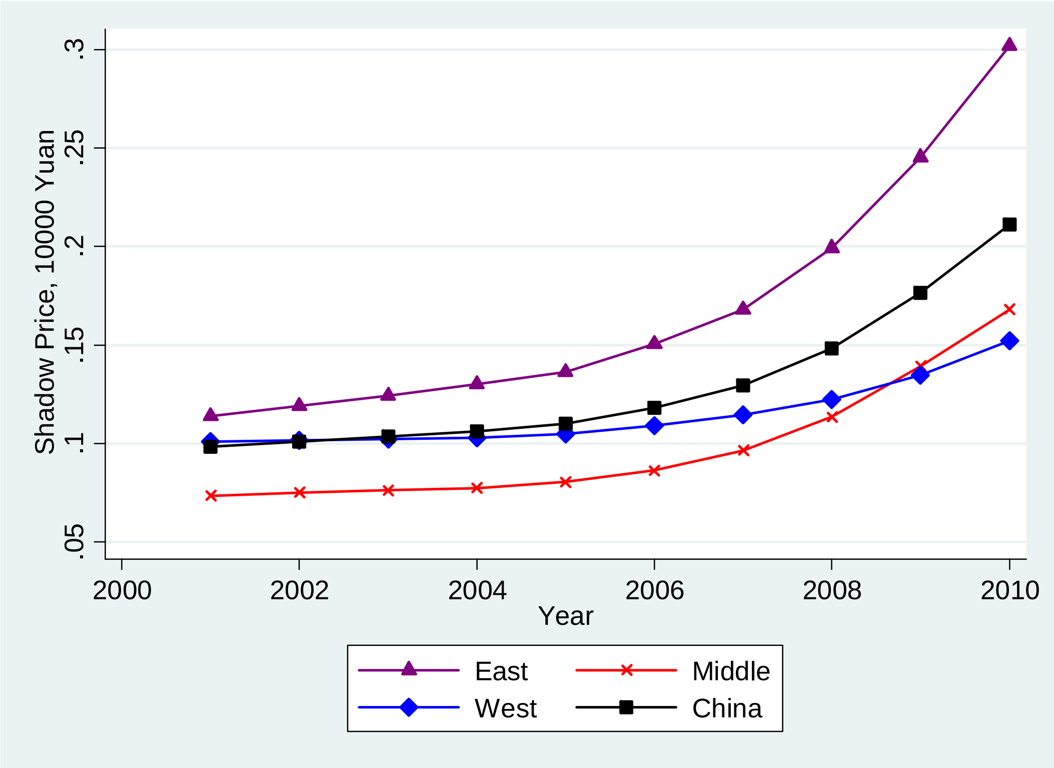

Figure 6: Average Shadow Price by Region

Figure 6 furthermore plots the average shadow prices of the three different regions and the whole country (more detailed shadow price estimates are reported in Appendix Table 3A). From the figure, we can observe that the average shadow price of CO_2 abatement for the whole country of China has increased continuously and sharply for the period 2001 to 2010. Specifically, this increase amounted to about 1000 Yuan/ton in 2001 to more than 2000 Yuan/ton in 2010. This corresponds to an annual growth rate of about 8%. To put this figure in context, the growth rate of the shadow price during period 2006 to 2010 is significantly higher than growth in the earlier period. The regional shadow prices are unbalanced. The average shadow price of east region is much higher than that of the west and middle regions. It indicates that it is more expensive for the east region to control the CO_2 emissions compared with the middle and west regions. This makes sense, since the carbon intensity of the east region is much higher than that of the west and middle regions.

Table 2 compares our results with those of previous studies. The results of these previous studies lie in a pretty wide range depending on their usage of different dataset and estimation method.

Table 2: Comparison with Previous Studies

studies	Method	Period	Sample	Shadow Price (mean)
Wang et al. (2011)	DEA	2007	30 provinces	475.3 Yuan/ton
Choi et al. (2012)	DEA	2001-2010	30 provinces	6.54-7.44 dollars/ton
Lee and Zhang (2012)	SDF+LP	2009	30 industries	3.13 dollars/ton
Yuan et al. (2012)	DEA	2004, 2008	24 industries	200-120300 Yuan/ton
Wei et al. (2012)	DEA	1995-2007	30 provinces	114 Yuan/ton
Wei et al. (2013)	DDF+LP DDF+LM	2004	124 power plants	2059.8 Yuan/ton 612.6 Yuan/ton
This study	DDF+LP	2001-2010	30 provinces	1000-2100 Yuan/ton

Note: SDF, DDF, LP, LM, DEA denote Shephard Distance Function, Directional Distance Function, Linear Programming, Maximum Likelihood, Data Envelopment Analysis, respectively.

Wang et al. (2011) find that the average provincial shadow price of China is about 475 Yuan/ton in 2007, Wei et al. (2012) report a mean provincial shadow price of 114 Yuan/ton over the period 1995-2007, Choi et al. (2012) find that the average provincial shadow price lies in the range of 6.54-7.44 dollars/ton during the period 2001-2010, Lee and Zhang (2012) report an even lower average shadow price of 3.13 dollars/ton for 30 Chinese manufacturing industries, while Yuan et al. (2012) report a range of 200-120300 Yuan/ton for 24 industries. Our result is much higher than these studies. In more recent studies, Wei et al. (2013) report a mean shadow price of 2059.8 Yuan/ton (linear programming estimation) and 612.6 Yuan/ton (maximum likelihood estimation) for power plants in Zhejiang Province which is much closer to our estimation, using a similar methodology to ours (directional output distance function parameterized as quadratic functional form).

Different methodologies employed in these studies are one of the main reasons for disparities in the estimated shadow prices. In parametric estimations, results obtained from Shephard/translog specifications (proportional expansion of good and bad outputs) are consistently lower than results obtained using the directional/quadratic specification (expansion of good output and simultaneous contraction of bad output). This is because the former estimation technique places the DMUs on a less steep portion of the production frontier than the latter (Färe et al., 2005; Vardanyan and Noh, 2006). For those using DEA, some of the efficient observations must be located on the inflection points, which means that there is no unique slope to the frontier at those points. Consequently, the choice of slope will considerably affect the scale of the shadow price (Lee et al., 2002). Additionally, the dataset and sample period also may affect the results of the studies.

6.4 Morishima Elasticity of Substitution

We are also able to calculate the Morishima elasticity of substitution according to equation (17) once the parameters have been estimated.

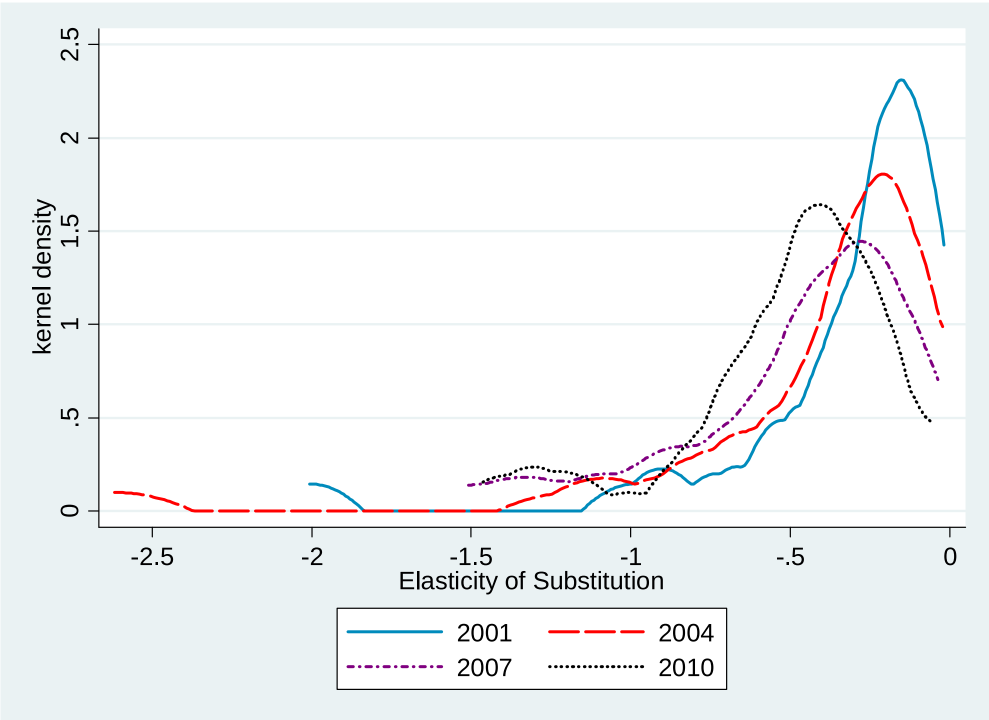

Figure 7: Kernel Density of Morishima Elasticity

Figure 7 plots the kernel density of provincial Morishima elasticities for selected years (more detailed estimates of Morishima elasticity are reported in Appendix Table 4A). From the figure, we can observe that the kernel density curve shifts leftward, which means that the average absolute value of the substitution elasticity has increased over time. In other words, it has become more costly for the provinces in China to reduce CO_2 emissions as time passes.

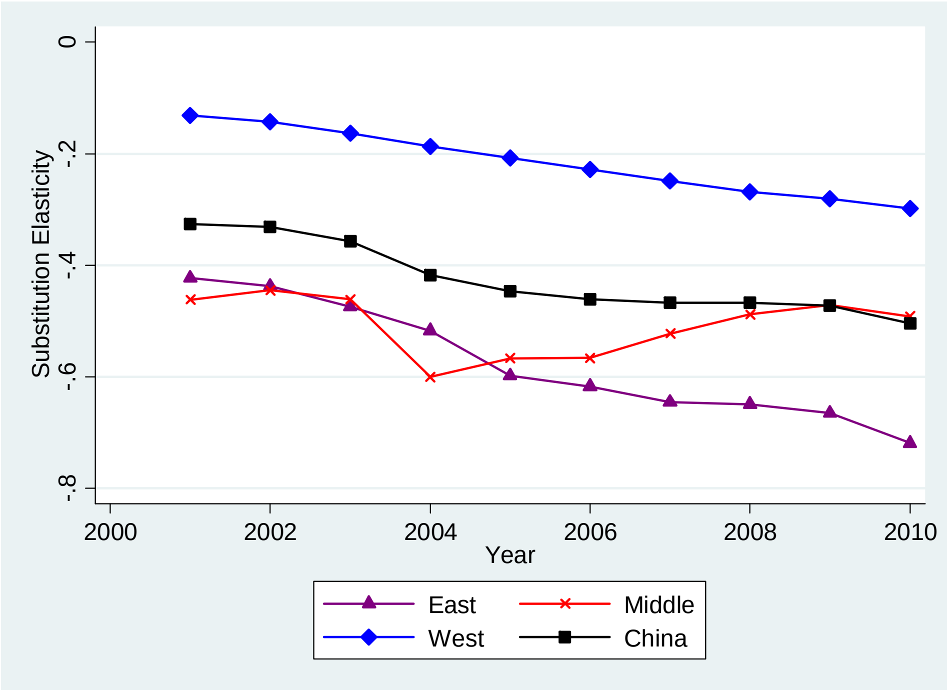

Figure 8: Average Elasticity of Substitution by Region

Figure 8 furthermore plots the evolution of regional average Morishima elasticities. From the figure, we observe that the average substitution elasticity (absolute value) increased continuously for all the three regions and the whole country, indicating an increasing cost of CO_2 abatement. Although the ratio of GDP to CO_2 emissions (y/b) has increased from 4293 Yuan/ton in 2001 to 5254 Yuan/ton in 2010 for China, we can expect that it will be more difficult to increase this ratio still further. Any further increases in the ratio can only be brought about by much higher penalties on CO_2 emissions. The substitution elasticity of the east region is much higher than that of the west and middle region (for most years) respectively.

7. Conclusion

This paper investigates the technical inefficiency, shadow price and Morishima substitution elasticity of CO_2 emissions in China, based on a provincial panel dataset covering the years 2001-2010. The directional output distance function is parameterized as a quadratic functional form and the parameters are estimated by a linear programming algorithm. GDP represents the good output and CO_2 emissions the bad output. Moreover labor, capital stocks and energy consumption comprise the three different inputs.

Overall we find that China's technical inefficiency of China increased continuously during the periods 2001 to 2010 when we integrate CO_2 emissions into the production technology. Generalizing, it is possible to reduce the CO_2 emissions by 4.5%, corresponding to 0.86 billion tons, for the period 2001 to 2005 if all the provinces were to produce on the production frontier. For the period of 2006 to 2010, the reduction potential increased to 4.9%, corresponding to a CO_2 emissions reduction of about 1.6 billion tons. We also find that the shadow price of CO_2 reduction in China has increased continuously during the whole sample period, and the speed of this increase has accelerated. For the period of the 2001 to 2005, the shadow price increased slightly from 1000 Yuan/ton to 1100 Yuan/ton, while for the period 2006 to 2010 it increased dramatically from 1200 Yuan/ton to 2100 Yuan/ton. Moreover, the shadow prices of the three regions are highly heterogeneous. The east region has a much higher average shadow price than that of the middle and west regions. This has mostly to do with the different industrial composition across the regions with the burden of heavy, dirty industry located in the west.

Finally, we find that the average absolute value of the Morishima substitution elasticity in China has also risen progressively during the sample period. This means that it has become more costly for China to further reduce CO_2 emissions. The substitution elasticity of the three regions is similarly very heterogeneous. The east region has a much higher elasticity than the west region (in line with the high ratio of services industries located here), as well of that for the middle region (for most years).

Our results have important policy implications. First, our results demonstrate that there is scope for further CO_2 reductions and simultaneous GDP expansion for China if all the provinces were to produce on the production frontier. Opportunities for 'double dividend' do indeed exist. This can be achieved, in our view, if policy-makers provide more incentives to push the firms within their regions to promote efficiency. Secondly, the Chinese government is planning to establish domestic carbon tax and CO_2 emissions trading market. Our estimation of the shadow prices may moreover provide a yardstick which the government can use when fixing these tax rates and ascertaining an initial market price for the trading system. Thirdly, to achieve the reduction target of CO_2 emissions, the central government of China placed the burden of making these reductions on the regional governments. From the view of minimizing the social abatement cost, consideration should we taken of the different abatement costs for each province when making these allocations. For instance, provinces should have their reduction burdens brought into line with their different marginal abatement costs. Finally, our results indicate that it is increasingly more costly for China to further reduce CO_2 emissions. This insight may help to inform the ongoing debate between the Chinese government and the community on climate change.

References

Aigner, D.J., Chu, S.F., 1968. On estimating the industry production function. The American Economic Review 58, 826-839.

Blackorby, C., Russell, R.R., 1981. The Morishima elasticity of substitution; symmetry, constancy, separability, and its relationship to the Hicks and Allen elasticities. The Review of Economic Studies 48, 147-158.

Boyd, G., Molburg, J., Prince, R., 1996. Alternative methods of marginal abatement cost estimation: non-parametric distance functions, 17. Annual North American conference of the International Association for Energy Economics. Argonne National Lab., IL (United States). Decision and Information Sciences Div., Boston, MA (United States).

Boyd, G.A., Tolley, G., Pang, J., 2002. Plant level productivity, efficiency, and environmental performance of the container glass industry. Environmental and Resource Economics 23, 29-43.

Chambers, R., Chung, Y., Färe, R., 1998. Profit, directional distance functions, and Nerlovian efficiency. Journal of Optimization Theory and Applications 98, 351-364.

Chen, W.Y., 2005. The costs of mitigating carbon emissions in China: findings from China MARKAL-MACRO modeling. Energy Policy 33, 885-896.

Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO2 emissions in China: a slacks-based efficiency measure. Applied Energy 98, 198-208.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. Journal of Environmental Management 51, 229-240.

Coggins, J.S., Swinton, J.R., 1996. The price of pollution: a dual approach to valuing SO allowances. Journal of Environmental Economics and Management 30, 5872.

Criqui, P., Mima, S., Viguier, L., 1999. Marginal abatement costs of CO2 emission reductions, geographical flexibility and concrete ceilings: an assessment using the POLES model. Energy Policy 27, 585-601.

Du, L.-M., Wei, C., Cai, S.-H., 2012. Economic development and carbon dioxide emissions in China: provincial panel data analysis. China Economic Review 23, 371-384.

Färe, R., Grosskopf, S., Lovell, C.A.K., Yaisawarng, S., 1993. Derivation of shadow prices for undesirable outputs: a distance function approach. The Review of Economics and Statistics 75, 374-380.

Färe, R., Grosskopf, S., Noh, D.-W., Weber, W., 2005. Characteristics of a polluting technology: theory and practice. Journal of Econometrics 126, 469-492.

Färe, R., Grosskopf, S., Pasurka, J.C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32, 1055-1066.

Färe, R., Grosskopf, S., Weber, W.L., 2006. Shadow prices and pollution costs in U.S. agriculture. Ecological Economics 56, 89-103.

Fischer, C., Morgenstern, R.D., 2006. Carbon abatement costs: why the wide range of estimates? The Energy Journal 27, 73-86.

IPCC, 2006. 2006 IPCC guidelines for national greenhouse gas inventories. Intergovernmental Panel on Climate Change.

Kaneko, S., Fujii, H., Sawazu, N., Fujikura, R., 2010. Financial allocation strategy for the regional pollution abatement cost of reducing sulfur dioxide emissions in the thermal power sector in China. Energy Policy 38, 2131-2141.

Ke, T.-Y., Hu, J.-L., Li, Y., Chiu, Y.-H., 2008. Shadow prices of SO2 abatements for regions in China. Agricultural and Resources Economics 5, 59-78.

Ke, T.-Y., Hu, J.-L., Yang, W.-J., 2010. Green inefficiency for regions in China. Journal of Environmental Protection 1, 330-336.

Lee, J.-D., Park, J.-B., Kim, T.-Y., 2002. Estimation of the shadow prices of pollutants with production/environment inefficiency taken into account: a nonparametric directional distance function approach. Journal of Environmental Management 64, 365-375.

Lee, M., Zhang, N., 2012. Technical efficiency, shadow price of carbon dioxide emissions, and substitutability for energy in the Chinese manufacturing industries. Energy Economics 34, 1492-1497.

Maradan, D., Vassiliev, A., 2005. Marginal costs of carbon dioxide abatement: empirical evidence from cross-country analysis. Revue Suisse d Economie et de Statistique 141, 377-410.

Marklund, P.-O., Samakovlis, E., 2007. What is driving the EU burden-sharing agreement: Efficiency or equity? Journal of Environmental Management 85, 317-329.

Morris, J., Paltsev, S., Reilly, J., 2012. Marginal Abatement Costs and Marginal Welfare Costs for Greenhouse Gas Emissions Reductions: Results from the EPPA Model. Environmental Modeling & Assessment 17, 325-336.

Murty, M., Kumar, S., Dhavala, K., 2007. Measuring environmental efficiency of industry: a case study of thermal power generation in India. Environmental and Resource Economics 38, 31-50.

Reig-Martínez, E., Picazo-Tadeo, A., Hernández-Sancho, F., 2001. The calculation of shadow prices for industrial wastes using distance functions: an analysis for Spanish ceramic pavements firms. International Journal of Production Economics 69, 277-285.

Rosenthal, E., 2008. China Increases Lead as Biggest Carbon Dioxide Emitter, New York Times.

Shephard, R.W., Gale, D., Kuhn, H.W., 1970. Theory of cost and production functions.

Princeton University Press Princeton, NJ.

Swinton, J.R., 1998. At what cost do we reduce pollution? Shadow prices of SO2 emissions. The Energy Journal 19, 63-83.

Swinton, J.R., 2002. The potential for cost savings in the sulfur dioxide allowance market: empirical evidence from Florida. Land Economics 78, 390-404.

Swinton, J.R., 2004. Phase I completed: an empirical assessment of the 1990 CAAA. Environmental and Resource Economics 27, 227-246.

Tol, R.S.J., 1999. The marginal costs of greenhouse gas emissions. The Energy Journal 20, 61-81.

Tu, Z.-G., 2010. The shadow price of industrial SO2 emission: a new analytic framework. China Economic Quarterly 1, 259-282.

Vardanyan, M., Noh, D.-W., 2006. Approximating pollution abatement costs via alternative specifications of a multi-output production technology: a case of the US electric utility industry. Journal of Environmental Management 80, 177-190.

Wang, Q.-W., Cui, Q.-J., Zhou, D.-Q., Wang, S.-S., 2011. Marginal abatement costs of carbon dioxide in China: a nonparametric analysis. Energy Procedia 5, 2316-2320.

Wei, C., Andreas, L., Liu, B., 2013. An empirical analysis of the CO2 shadow price in Chinese thermal power enterprises. Energy Economics forthcoming.

Wei, C., Ni, J., Du, L., 2012. Regional allocation of carbon dioxide abatement in China. China Economic Review 23, 552-565.

Yuan, P., Liang, W.-B., Cheng, S., 2012. The margin abatement costs of CO2 in Chinese industrial sectors. Energy Procedia 14, 1792-1797.

Zhang, J., Wu, G.-Y., Zhang, J.-P., 2004. The estimation of China's provincial capital stock: 1952-2000. Economic Research Journal 10, 35-44.

Zhang, Z.X., Folmer, H., 1998. Economic modelling approaches to cost estimates for the control of carbon dioxide emissions. Energy Economics 20, 101-120.

Appendix:

Table 1A: Parameter Estimates of Directional Distance Function

Parameters	Estimates	Parameters	Estimates	Parameters	Estimates	Parameters	Estimates
α_0	-0.02	α_{11}	0.69	α_{31}	0.37	η_2	0.20
α_1	-0.01	α_{12}	-0.23	α_{32}	-0.30	η_3	0.00
α_2	0.54	α_{13}	0.37	α_{33}	0.07	μ	-0.06
α_3	-0.15	α_{21}	-0.23	β_2	-0.06	δ_1	-0.10
β_1	-0.76	α_{22}	-0.03	γ_2	-0.06	δ_2	0.20
γ_1	0.24	α_{23}	-0.30	η_1	-0.10	δ_3	0.00

Table 2A: Estimates of Directional Output Distance Functions, 2001-2010

	10th Five-year Plan					11th Five-year Plan				
Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Beijing	0.11	0.11	0.10	0.08	0.07	0.06	0.05	0.03	0.00	0.00
Tianjin	0.05	0.04	0.03	0.02	0.01	0.00	0.00	0.01	0.03	0.06
Hebei	0.00	0.01	0.01	0.01	0.05	0.03	0.00	0.02	0.10	0.01
Shanxi	0.00	0.02	0.03	0.01	0.00	0.02	0.02	0.07	0.10	0.14
Inner Mongolia	0.00	0.00	0.00	0.03	0.04	0.07	0.10	0.17	0.23	0.31
Liaoning	0.08	0.04	0.02	0.00	0.03	0.02	0.02	0.02	0.03	0.08
Jilin	0.02	0.02	0.00	0.00	0.02	0.05	0.08	0.14	0.19	0.28
Heilongjiang	0.13	0.11	0.09	0.06	0.04	0.03	0.01	0.01	0.00	0.00
Shanghai	0.20	0.18	0.15	0.11	0.09	0.06	0.02	0.00	0.02	0.02
Jiangsu	0.09	0.01	0.00	0.01	0.08	0.09	0.07	0.10	0.15	0.35
Zhejiang	0.02	0.01	0.00	0.01	0.04	0.08	0.10	0.09	0.12	0.13
Anhui	0.05	0.04	0.03	0.01	0.00	0.01	0.01	0.00	0.01	0.04
Fujian	0.02	0.02	0.01	0.01	0.02	0.00	0.00	0.02	0.04	0.02
Jiangxi	0.00	0.00	0.00	0.01	0.02	0.02	0.03	0.02	0.00	0.02
Shandong	0.00	0.01	0.05	0.07	0.26	0.18	0.11	0.08	0.00	0.10
Henan	0.03	0.00	0.02	0.09	0.09	0.08	0.05	0.02	0.00	0.01
Hubei	0.00	0.00	0.02	0.03	0.04	0.04	0.03	0.03	0.04	0.05
Hunan	0.00	0.00	0.03	0.06	0.14	0.13	0.11	0.07	0.04	0.02
Guangdong	0.19	0.11	0.05	0.00	0.06	0.05	0.02	0.00	0.06	0.11
Guangxi	0.01	0.00	0.00	0.02	0.03	0.03	0.03	0.04	0.05	0.12
Hainan	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.02	0.01	0.02
Chongqing	0.01	0.01	0.00	0.00	0.02	0.02	0.02	0.06	0.03	0.01
Sichuan	0.01	0.00	0.06	0.09	0.11	0.12	0.12	0.14	0.08	0.00
Guizhou	0.00	0.00	0.04	0.07	0.08	0.10	0.11	0.11	0.13	0.15
Yunnan	0.00	0.01	0.01	0.00	0.07	0.10	0.13	0.14	0.14	0.18
Shaanxi	0.00	0.02	0.03	0.02	0.03	0.03	0.03	0.05	0.06	0.12
Gansu	0.00	0.01	0.02	0.02	0.02	0.03	0.04	0.06	0.05	0.07
Qinghai	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.03	0.03	0.03
Ningxia	0.00	0.00	0.01	0.02	0.03	0.04	0.05	0.08	0.09	0.12
Xinjiang	0.00	0.00	0.00	0.01	0.01	0.02	0.04	0.05	0.07	0.08
East	0.07	0.05	0.04	0.03	0.06	0.05	0.04	0.04	0.05	0.08
Middle	0.03	0.02	0.03	0.03	0.04	0.05	0.04	0.04	0.05	0.07
West	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.08	0.09	0.11
China	0.03	0.03	0.03	0.03	0.05	0.05	0.05	0.06	0.06	0.09

Note: 1) Mean values of provincial inefficiencies in each year are reported in the table for the whole country and three different regions.

Table 3A: Estimates of Shadow Prices, 2001-2010, 10000 Yuan

	10th Five-year Plan					11th Five-year Plan				
Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Beijing	0.16	0.16	0.17	0.18	0.19	0.20	0.22	0.23	0.25	0.27
Tianjin	0.14	0.14	0.15	0.15	0.16	0.16	0.18	0.19	0.22	0.26
Hebei	0.06	0.06	0.06	0.06	0.05	0.06	0.08	0.10	0.13	0.16
Shanxi	0.07	0.07	0.07	0.07	0.07	0.08	0.08	0.09	0.11	0.12
Inner Mongolia	0.10	0.10	0.10	0.09	0.10	0.10	0.11	0.12	0.15	0.19
Liaoning	0.11	0.11	0.11	0.12	0.12	0.14	0.15	0.22	0.26	0.31
Jilin	0.11	0.11	0.11	0.11	0.11	0.13	0.15	0.18	0.22	0.26
Heilongjiang	0.10	0.11	0.11	0.11	0.11	0.11	0.12	0.13	0.15	0.17
Shanghai	0.18	0.19	0.20	0.20	0.21	0.23	0.25	0.28	0.31	0.34
Jiangsu	0.11	0.12	0.14	0.15	0.16	0.20	0.24	0.30	0.42	0.58
Zhejiang	0.10	0.11	0.12	0.14	0.16	0.17	0.19	0.23	0.28	0.33
Anhui	0.05	0.05	0.05	0.06	0.06	0.07	0.07	0.08	0.09	0.10
Fujian	0.12	0.12	0.12	0.12	0.13	0.13	0.15	0.17	0.19	0.23
Jiangxi	0.09	0.09	0.10	0.10	0.10	0.11	0.12	0.13	0.14	0.15
Shandong	0.07	0.07	0.08	0.09	0.08	0.11	0.14	0.19	0.29	0.42
Henan	0.01	0.02	0.02	0.02	0.02	0.03	0.05	0.09	0.15	0.22
Hubei	0.08	0.09	0.09	0.09	0.10	0.10	0.11	0.13	0.15	0.17
Hunan	0.06	0.06	0.07	0.06	0.06	0.06	0.07	0.09	0.11	0.14
Guangdong	0.08	0.09	0.09	0.09	0.10	0.11	0.12	0.15	0.21	0.28
Guangxi	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.11	0.13	0.17
Hainan	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15
Chongqing	0.10	0.10	0.11	0.11	0.12	0.12	0.13	0.14	0.15	0.16
Sichuan	0.05	0.05	0.05	0.05	0.06	0.07	0.08	0.09	0.11	0.14
Guizhou	0.08	0.08	0.08	0.07	0.07	0.07	0.07	0.08	0.08	0.09
Yunnan	0.11	0.11	0.11	0.11	0.10	0.10	0.11	0.11	0.12	0.14
Shaanxi	0.10	0.10	0.11	0.11	0.11	0.12	0.13	0.15	0.17	0.20
Gansu	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11	0.12	0.12
Qinghai	0.13	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15
Ningxia	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.14	0.14
Xinjiang	0.13	0.14	0.14	0.14	0.14	0.15	0.15	0.16	0.16	0.17
East	0.11	0.12	0.12	0.13	0.14	0.15	0.17	0.20	0.25	0.30
Middle	0.07	0.08	0.08	0.08	0.08	0.09	0.10	0.11	0.14	0.17
West	0.10	0.10	0.10	0.10	0.10	0.11	0.11	0.12	0.13	0.15
China	0.10	0.10	0.10	0.11	0.11	0.12	0.13	0.15	0.18	0.21

Note: 1) the mean values of provincial shadow price in each year are reported in the table for the three regions and whole country.

Table 4A: Estimates of the Morishima Elasticity, 2001-2010

	10th Five-year Plan					11th Five-year Plan				
Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Beijing	-0.23	-0.25	-0.26	-0.28	-0.30	-0.33	-0.36	-0.38	-0.40	-0.43
Tianjin	-0.12	-0.13	-0.14	-0.16	-0.17	-0.19	-0.21	-0.24	-0.27	-0.31
Hebei	-0.55	-0.60	-0.67	-0.74	-0.93	-0.91	-0.87	-0.81	-0.79	-0.75
Shanxi	-0.17	-0.22	-0.26	-0.28	-0.29	-0.33	-0.37	-0.40	-0.38	-0.41
Inner Mongolia	-0.11	-0.13	-0.15	-0.20	-0.24	-0.29	-0.33	-0.39	-0.42	-0.45
Liaoning	-0.30	-0.31	-0.34	-0.36	-0.41	-0.44	-0.47	-0.46	-0.50	-0.56
Jilin	-0.13	-0.14	-0.15	-0.17	-0.20	-0.22	-0.24	-0.27	-0.30	-0.34
Heilongjiang	-0.26	-0.26	-0.27	-0.29	-0.31	-0.33	-0.35	-0.38	-0.38	-0.41
Shanghai	-0.30	-0.32	-0.33	-0.36	-0.38	-0.40	-0.44	-0.47	-0.50	-0.54
Jiangsu	-0.63	-0.62	-0.66	-0.73	-0.82	-0.87	-0.93	-0.99	-1.08	-1.29
Zhejiang	-0.46	-0.48	-0.51	-0.56	-0.60	-0.66	-0.73	-0.75	-0.78	-0.84
Anhui	-0.35	-0.36	-0.38	-0.39	-0.41	-0.44	-0.47	-0.49	-0.52	-0.56
Fujian	-0.23	-0.25	-0.27	-0.29	-0.33	-0.36	-0.39	-0.42	-0.45	-0.47
Jiangxi	-0.15	-0.16	-0.18	-0.21	-0.23	-0.25	-0.27	-0.29	-0.30	-0.34
Shandong	-0.82	-0.84	-0.92	-1.00	-1.27	-1.16	-1.14	-1.11	-1.06	-1.17
Henan	-2.01	-1.75	-1.70	-2.62	-2.09	-1.90	-1.35	-0.97	-0.78	-0.73
Hubei	-0.28	-0.29	-0.33	-0.36	-0.40	-0.42	-0.46	-0.48	-0.51	-0.55
Hunan	-0.35	-0.37	-0.41	-0.49	-0.62	-0.64	-0.66	-0.62	-0.60	-0.60
Guangdong	-0.98	-0.98	-1.07	-1.17	-1.32	-1.42	-1.51	-1.44	-1.41	-1.46
Guangxi	-0.18	-0.19	-0.21	-0.24	-0.27	-0.29	-0.32	-0.33	-0.33	-0.36
Hainan	-0.03	-0.04	-0.04	-0.04	-0.04	-0.05	-0.05	-0.07	-0.07	-0.08
Chongqing	-0.13	-0.14	-0.15	-0.16	-0.18	-0.20	-0.22	-0.26	-0.27	-0.30
Sichuan	-0.47	-0.49	-0.59	-0.65	-0.66	-0.68	-0.70	-0.69	-0.68	-0.66
Guizhou	-0.09	-0.10	-0.13	-0.16	-0.18	-0.22	-0.24	-0.24	-0.27	-0.29
Yunnan	-0.13	-0.14	-0.16	-0.17	-0.22	-0.25	-0.28	-0.30	-0.32	-0.34
Shaanxi	-0.14	-0.16	-0.18	-0.20	-0.22	-0.23	-0.26	-0.29	-0.31	-0.35
Gansu	-0.07	-0.08	-0.10	-0.11	-0.12	-0.13	-0.15	-0.16	-0.17	-0.19
Qinghai	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.04	-0.05	-0.05	-0.06
Ningxia	-0.02	-0.02	-0.03	-0.03	-0.04	-0.05	-0.06	-0.07	-0.08	-0.09
Xinjiang	-0.08	-0.09	-0.10	-0.11	-0.12	-0.14	-0.15	-0.17	-0.19	-0.20
East	-0.42	-0.44	-0.47	-0.52	-0.60	-0.62	-0.65	-0.65	-0.66	-0.72
Middle	-0.46	-0.44	-0.46	-0.60	-0.57	-0.57	-0.52	-0.49	-0.47	-0.49
West	-0.13	-0.14	-0.16	-0.19	-0.21	-0.23	-0.25	-0.27	-0.28	-0.30
China	-0.33	-0.33	-0.36	-0.42	-0.45	-0.46	-0.47	-0.47	-0.47	-0.50